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# Market Frictions, Demand Structure and Price Competition in Online Markets

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# MARKET FRICTIONS, DEMAND STRUCTURE AND PRICE COMPETITION IN ONLINE MARKETS

*Frictions du marché, structure de la demande et concurrence en prix dans les marchés en ligne*

## Completed Research Paper

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## Abstract

*Recent empirical evidence shows the Law of One Price does not exist in online environment despite the unprecedented amount of price transparency. The failure of Law of One Price has been attributed to search costs, brand loyalty and other kinds of “market frictions” that enable retailers to keep some of their customers even if they don’t charge the lowest price in the market. While the presence of such frictions has been carefully studied, little is known empirically on how they affect consumer demand structure that is at the core of retailers’ pricing and marketing strategies. In this paper, we identify the impact of market friction on demand structure by empirically demonstrating a well-known insight from economic theory that market frictions could lead to a kink in consumer demand function. Using a unique dataset on prices and demand collected from Amazon and BarnesandNoble.com (BN), we first demonstrate the existence of consumer segments that demonstrate significant amount of frictions against shopping for lowest prices. Then we incorporate this finding and build an empirical model to show that significant jumps in price elasticity exist at points where price changes occur, which in turn, manifests as kinks in the aggregate demand function. Moreover, the jumps have opposite directions on Amazon and BN, indicating that market frictions have different implications across the two major online retailers. By examining kinks in demand functions, we contribute to prior empirical literature that has typically considered a constant level of price elasticity. We find that, on Amazon, price elasticity increases after a price reduction, suggesting that customers face low search costs for price information on Amazon or low brand loyalty toward BN. On the other hand, price elasticity decreases after a price reduction on BN, suggesting customers face high search costs for price information on BN or high brand loyalty towards Amazon. Further, an analysis of the differences in jumps in price elasticity for popular books compared to rare or unpopular books reveals that market friction is much higher for unpopular books. These findings suggest that online retailers have the potential to extract more value from the emergence of the Long Tail phenomenon.*

**Keywords:** Electronic Markets, Search Costs, Kinked Demand Curve, Price Elasticity, Price Competition, Product Variety, Product Popularity

## Résumé

*La littérature existante a montré que les coûts de recherche, la fidélité à la marque et d'autres "frictions de marché" permettent aux distributeurs de garder certains de leurs clients même s'ils ne proposent pas les prix le plus bas du marché. Alors que la présence de telles frictions de marché a été soigneusement étudiée, nous savons empiriquement peu sur la manière dont elles affectent la structure de la demande des consommateurs. Dans ce papier, nous estimons économétriquement l'impact de la friction de marché sur la structure de la demande. Nous testons nos modèles en utilisant des données relatives aux prix et à la demande collectées sur les sites d'Amazon et de BarnesandNoble.com.*

## Introduction

An important advantage that electronic markets posit over physical markets is a reduction in search costs for product-related information such as prices. Unlike in a physical market where consumers need to travel to multiple stores for price comparison, competitors' prices are just a few clicks away in an online market. The emergence of online shopbots such as Froogle, Pricegrabber, Dealtime, etc. have further reduced consumer search costs by presenting price information for the same product from multiple online vendors. The reduction in price search cost has rekindled interests in examining the Law of One Price (Brynjolfsson and Smith 2000). Theoretical research has shown that search costs create incomplete information about firms' prices among consumers, which leads to equilibrium price dispersion in otherwise homogeneous product markets (Reinganum 1979, Stahl 1989). This phenomenon has been observed in conventional retail markets where consumers must incur the incremental costs of searching for prices at firms' brick-and-mortar stores. As the internet reduces search costs, price dispersion was expected to disappear and the Law of One Price was predicted to prevail.<sup>1</sup>

Empirical evidence however shows that there is significant price dispersion online (Brynjolfsson and Smith 2000, Baye et al. 2004, Baye et al. 2006). Such empirical evidence on price dispersion calls attention for a more detailed examination of the online market. Studies show that the failure of the Law of One Price can be attributed to search costs, brand loyalty and other "market frictions" that enables a retailer to keep some of its customers even if it does not charge the lowest price in the market. The presence of these market frictions affects a retailer's optimal pricing and competitive strategies. A consumer with high search costs or high brand loyalty repeatedly buys from the same firm over successive purchase occasions because she is uninformed of competitive prices or because she does not care. As a result, the retailer can charge high price and obtain positive profits from these customers. On the other hand, a retailer can choose to charge the lowest price to attract informed consumers. The presence of market frictions therefore significantly enriches market competition and brings about new pricing and market strategies (Varian 1980, Narasimhan 1988). More generally, theories from information economics such as Stiglitz (1989) suggest that due to the presence of market frictions, a retailer could face different price elasticities for price decreases versus price increases, leading to a change in the slope of the consumer demand function (also known as a kink in demand curve). Such differences in price elasticities is an important strategic consideration for retailers since it dictates the net impact of market frictions on firm profits - whether the competition intensifying effect dominates the market expansion effect or vice-versa.

The objective of our paper is to empirically examine how market frictions affect the nature of demand function. We abstract away from the underlying causes of market frictions to focus on the consequence of market frictions. Moreover, by focusing on the structure of the demand function, we are able to analyze how differences between sellers as well as within products moderate the influence of market frictions. For example, price information from retailers on popular products is likely to be widely available online and thereby limit the impact of search costs on

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<sup>1</sup> The relationship between price dispersion and search costs is not necessarily monotonous. Brown and Goolsbee (2002) shows that price dispersion first increases and then decreases with the reduction of search costs, consistent with earlier theoretical findings (e.g. MacMin 1980)

consumers. On the other hand, price information from retailers on unpopular or niche products is more likely to be harder to locate, thereby exacerbating the impact of search costs creating more frictions in the market. By considering the consumer demand function for different products across the two major online book retailers, we are able to identify the role of seller and product characteristics in determining the potential impact of market frictions on competition between retailers.

Till date, empirical studies on retailing have implicitly assumed that retailers face a demand function with constant price elasticity for any kind of a price change (Chevalier and Goolsbee 2003, Ellison and Ellison 2004, Ghose et al. 2006), and used the estimated price elasticity to make inferences about competition and welfare in online marketplaces. This approach, however, does have a limitation. The assumption of constant price elasticity could lead to biased estimates if the difference in price elasticity for price changes in opposite directions is large. For example, if a retailer faces low price elasticity for price increases, but high price elasticity for price reductions, the constant elasticity assumption will average the price elasticity, thereby underestimating the real competitiveness and sensitivity in the market. By considering how price elasticity changes as retailers adjust product prices, this study expands our understanding of online competition and the role of market frictions in influencing the competition. One exception to the constant elasticity assumption is a recent study by Baye et al. (2006) which shows that price elasticity on shopbots increases dramatically after a retailer reduces its price to become the lowest price firm on the market. Their result provides support for a special case of Stiglitz (1989) with extremely low search costs. Our study expands the implications of the Baye et al. (2006) paper to a more general case where price elasticity changes at any point where price is adjusted.

Our data on prices and demand come from the two largest online books retailers, Amazon and Barnes and Noble.com (BN). These two retailers account for nearly 90% of the online book retailing market (Lattovich and Smith 2001), thus making our analysis applicable to general online markets. A key distinguishing feature of our study is that we conduct the demand analysis at the aggregate level, thereby providing an overall insight into the impact of market frictions on consumer demand. In this way, we complement prior studies that measure brand loyalty, search costs and other market frictions at the individual consumer level. These studies benefit from having detailed data on consumer search activities that allow for careful measure of cause of friction at the individual level. However, a potential limitation of these studies is that they primarily focused on shopbot users. As shopbot users typically incur less friction costs than an average online shopper, it is difficult to extrapolate the implications from those studies for understanding price competition between online retailers in general. Combining our study with these prior studies extends our understanding of the role of market frictions in online markets.

Our paper aims to make of the following contributions. First, we aim to advance our understanding of the impact of market frictions on consumer demand structure in electronic markets. By examining the impact of the composition of the market on price elasticities, we get better insights into the structure of competition between the two largest online retailers in the book industry. By highlighting the existence of a kink in the demand structure, and the consequent jumps in price elasticity at points where prices change, we contribute to both prior theoretical literature and empirical literature. From the perspective of prior empirical literature, we demonstrate that in markets with friction costs, price elasticity for price increases can be substantially different from that for price decreases. This is in contrast to prior work in online demand estimation that has typically considered a constant level of price elasticity for price increases as well as for price decreases. This can have useful implications for retailers' pricing strategies.

Second, we show how the impact of market frictions on consumers varies across the two major online retailers. Price elasticity is higher for price decreases than for price increases on Amazon, indicating that Amazon's price decrease information is quickly disseminated amongst consumers. This suggests either low search costs for Amazon's price information or low brand loyalty for BN. On the contrary, price elasticity is lower for price decreases than for price increases on BN, indicating that potential customers are not easily aware of its price change information. This suggests higher search costs incurred by customers for BN's price information or high brand loyalty towards Amazon. The combination of the two results implies that market frictions are ubiquitous in online markets but they vary across online retailers. Further, we demonstrate that price elasticity after a price reduction increases over time across a period of 4 weeks after the price change, suggesting that market frictions reduce over time. The finding that market frictions are dynamic over time can have practical implications for online retailers.

Third, our empirical analysis provides evidence that market frictions for popular books are much lower than that for less popular and niche books. The results imply that retailers are likely to face less aggravated price competition for

less popular or niche products even if competitors were to carry similar product assortments. This provides incentive for retailers to focus on niche products, further fostering the emergence of the Long Tail. This finding has implications on product variety in online markets.

The rest of the paper is as follows: Next, we present the theoretical framework based on which the empirical estimations are carried out. The data are described next. Thereafter, we provide the empirical methodology. Subsequently, we present the analysis of the impact of search costs on the demand structure for (i) the whole sample, (ii) for popular vs. unpopular books along with (iii) its impact on relative sales of Amazon.com and BarnesandNoble.com. We conclude with some discussion of implications and limitations of the paper.

## **Prior Literature and Theoretical Motivation**

The presence of market frictions in physical markets is well known. Electronic markets can reduce monetary costs of acquiring information. However, since information in online environments is highly visual and perceptual, it potentially increases cognitive costs that affect consumers' search for information (Chiang 2006). Furthermore, information search online is characterized by human-computer interaction requiring consumers to have increased ability and knowledge in acquiring information (Hodkison et al., 2000). As a result, the Internet can impose a certain degree of cognitive cost on consumers that could potentially prevent consumers from searching for more information.

A well-known feature of market frictions in a competitive marketplace is that it can create a kinked demand function (Stiglitz 1989) whose slope changes at points where a price change occurs. Stiglitz (1989) presents the model in the context of search costs, although the intuition applies to other types of market frictions as well. He shows that the presence of search costs may cause the demand elasticity for price reductions to be different from the demand elasticity for price increases. The extent of the kink is determined by the magnitude of friction costs faced by consumers. When search costs are high, consumers are only aware of the price of the retailer they visit, but are unaware of the prices for the same product in the retailers they do not visit. Consequently, when a retailer increases its price, its own immediate customers (who are aware of the increase) are induced to search for prices amongst rival retailers and the retailer loses customers accordingly. However, when a retailer decreases its price, then unless it expends resources on advertising, its action induces no new customers to launch a search. Hence, while it keeps its existing customers, it does not gain a proportionate number of new customers despite reducing the price. This leads to lower price elasticity for price reductions than price increases. Under such circumstances, the gains to lowering prices may be markedly lower than the losses from raising prices. On the other hand, when search costs are low, a reduction in product price by a retailer has the potential to attract customers from its competitors, but a price increase only affects the firm's own customers. This leads to higher price elasticity for price reductions than that for price increases. In this case, the gains from lowering prices could be much higher than the losses from raising prices. In sum, prior theories from the literature on information economics and search indicate that a retailer in a competitive environment faces different price elasticity for price increases than for price decreases. Not accounting for such differences could have major implications for retailers' pricing and assortment planning strategies.

While the presence of market frictions and their impact on consumer demand and retailer strategies has been well established theoretically, few empirical studies exist in this domain. The main focus of existing work has been to quantify these costs at the consumer level. Brynjolfsson, Dick and Smith (2004) found that the cost of an exhaustive search is about \$6.45 per consumer on a shopping bot. Hong and Shum (2006) develop a methodology for recovering search cost estimates using only observed price data. Bajari and Hortacsu (2003) quantified the cost of entering into an eBay auction to be \$3.20, which includes search costs and other friction costs related to auction participation. In a related stream of work, Hann and Terweisch (2003) discuss how frictional costs in electronic markets could be substantial and found that the median value of these costs ranging from EUR 3.54 for a portable digital music player (MP3) to EUR 6.08 for a personal digital assistant (PDA). However, these studies have largely focused on measuring market friction costs, with less attention being paid on how the frictions affect consumer demand structure or how they can affect retailers' pricing strategies.

We complement these studies by considering the impact of market frictions on demand function. Specifically, we analyze the magnitude of the kink in a firm's demand function. Our analysis also offers a new empirical explanation of a kinked demand curve that has been observed in prior literature. Theories from duopoly and oligopoly have long

suggested that kinks in demand function exist because competitors' responses to price changes could be asymmetric (Sweezy 1939, Maskin and Tirole 1988) as competitors are more likely to match a firm's price reductions but not price increases. Consequently, while a retailer may not accrue any gains in customers after a price reduction (due to competitors' price matching policies), it may lose a sizeable proportion of customers after a price increase. We show that a kinked demand function is not only caused by asymmetric price matching behavior by competitors (Bhaskar, Machin and Reid 1991), but also by market frictions which can lead to asymmetry in consumer responses to price changes. To separate the impact of the two types of kinked demand functions, we control for competitors' response and use the remaining kink in consumer demand to identify the impact of market frictions.

## Data

We estimate our models using a panel data set compiled from publicly available information about product prices and sales rankings, gathered using automated Java scripts. These scripts access and parse HTML and XML pages downloaded from Amazon.com and BN.com between September 2005 and April 2006. The panel includes daily data over 3210 books across all major book categories. These products include a mix of best sellers, new releases, random selected titles and less popular books selected from the different genres such as fiction, non-fiction, business, textbooks, computer books and so on.

We collect data from both Amazon.com and BN for the same set of books to control for competition among online retailers. In the context of online book sales, Amazon and BN are the two largest book retailers online, and their pricing policies influence each other. To control for competition from remaining online book retailers and used book markets, we also collected secondary market data that including the number of used copies available for sale for each of the books in our sample and the minimum price of the used books in Amazon's marketplace. We note that Amazon allows other book retailers like Abebooks and Powells to sell books on its marketplace. Thus, our data takes into account some of the competitive influence from other retailers.

Each observation from Amazon contains the date of data collection, the product's list price, its Amazon retail price, its Amazon sales rank (which serves as a proxy for units of demand, as described later), the date the product was released into the market, the average customer rating for the product, and the number of reviews based on which the average rating was computed. Each observation from BN contains similar aspects: the date of data collection, the product's list price, its BN retail price, its sales rank (which also serves as a proxy for units of demand, as described later), the average BN customer rating for the product, and the number of reviews based on which the average rating was computed.

The summary statistics of our data are in Table 1. It shows a significant amount of variation in the sample we use, covering a wide range of books with different online prices, sales ranks, secondary market information and release dates. The summary statistics also show that Amazon has significantly lower prices than BN and price changes on Amazon are more frequent than price changes on BN. These statistics provide some preliminary indications that consumers are likely to have a different level of friction costs for price information from Amazon than from BN, which allows Amazon to change price more often and give it more incentive to reduce prices.

<b>Table 1: Summary statistics for the data</b>					
<b>Variable</b>	<b>Obs.</b>	<b>Mean</b>	<b>Std Dev.</b>	<b>Min</b>	<b>Max</b>
Amazon Sales Rank	433443	196715.2	319355.5	1	3628125
Amazon Price	433443	19.42	22.09	2	299
Minimum Used Price	433443	14.35	20.70	.01	2069.94
Number of Used	433443	49.66	31.06	1	614
Amazon Rating	433443	4.30	0.72	1	5
Amazon_Number_Reviews	433443	24.65	129.07	1	3229
Amazon_Price Decrease	289810	0.89	0.32	0	1
BN Sales Rank	457836	99418.7	126015.2	1	724506

BN Price	457836	23.35	22.40	2.99	299
BN Rating	182047	4.46	0.76	0	5
BN Number_Reviews	182047	11.39	54.57	1	1179
BN_Price Decrease	239830	0.15	0.36	0	1

## Empirical Methodology

Our empirical analysis proceeds in two steps. In the first part, we build a parsimonious empirical model to uncover the demand structure in the market and infer the proportion of loyal customers and shoppers along with their respective price elasticities. Using maximum likelihood estimation techniques, our analysis highlights that there are differences in the price elasticities of loyal consumers and shoppers, which in turn will lead to a kink in the demand structure in accordance with prior economic theory. In the second part, we incorporate this finding about the presence of a kink in the demand structure and build an empirical model to examine the effect of this kink on the overall demand structure, on the differences of its impact across the two retailers, and on sales of popular versus less popular books.

### Testing the Composition of Consumers in the Market

An important feature of the nature of competition between firms is that it is shaped by the preferences of consumers in the market. Some consumers are loyal to one firm, others are loyal to the other firm and the remaining consumers are shoppers that switch between firms depending on who offers the lowest price. The presence of shoppers in a market can create a kink in the demand function. When one firm reduces its price below its competitor, it grabs all shoppers, leading to a discontinuity in the demand function. Moreover, inherent price elasticity also differs between loyal customers and shoppers. Therefore, the overall price elasticity when the firm tries to attract both loyal customers and shoppers could be very different from the average price elasticity of loyal customers only, which leads to a kink in the demand function.

The objective of this section is to provide an empirical model to uncover the demand structure in the market using observed sales data. This enables us to infer the proportion of loyal customers and shoppers, and their respective price elasticities. The setting of our empirical model is based on the standard ‘clearinghouse model’ (Varian 1980; Rosenthal 1988; Baye et al. 2006). Baye et al. (2006) show that the clearinghouse model is representative of a variety of economic environments where consumers face market friction such as search costs or brand loyalty. Our model assumes that there are three types of consumers in a market - loyal Amazon customers (or Amazon customers with high search cost) who only consider purchasing at Amazon; loyal BN customers (or BN customers with high search costs) who only consider purchasing at BN and shoppers who purchase from the firm offering the lowest price.

Let  $a$ ,  $b$  and  $s$  denote the proportion of Amazon customers, proportion of BN customers and the proportion of shoppers, in the market, respectively. Note that  $a + b + s = 1$ . Let the demand for a given product be given by its total market potential of  $M_i$ . The term market potential refers to the consumer demand for the product if its price is set to zero. Given our assumption of consumer segmentation,  $aM_i$  of the potential customers are loyal Amazon customers,  $bM_i$  are loyal BN customers, and  $sM_i$  are shoppers. The realized demand from each consumer is a function of both potential customers and the price they face. We use a log-log model to estimate realized demand for the three types of consumers and allow price elasticity  $e_a$ ,  $e_b$ , and  $e_s$  to differ across the three types of customers, where the subscript in ‘e’ denotes the customer type. The realized demand from each customer type can be written as follows:

Demand from ‘loyal Amazon’ customers:

$$\log(\text{Demand}_{a_{it}}) = \log(M_i) + \log(a) + e_a \log(\text{Amazon\_Price}_{it}) \quad (1a)$$

Demand from ‘loyal BN’ customers:

$$\log(\text{Demand}_{b_{it}}) = \log(M_i) + \log(b) + e_b \log(\text{BN\_Price}_{it}) \quad (1b)$$

Demand from ‘Shoppers’:

$$\log(\text{Demand}_{s_{it}}) = \log(M_i) + \log(s) + e_s \log(\min(\text{Amazon\_price}_{it}, \text{BN\_price}_{it})) \quad (1c)$$

Next we derive the realized demand at the two retailers. This is given as follows:

$$\begin{aligned} \text{Amazon demand}_{it} &= \text{Demand}_{a_{it}} + \text{Demand}_{s_{it}} * I(\text{Amazon\_Price}_{it} < \text{BN\_price}_{it}) \\ &= M_i \left( a(\text{Amazon\_Price}_{it})^{e_a} + s(\text{Amazon\_Price}_{it})^{e_s} I(\text{Amazon\_Price}_{it} < \text{BN\_Price}_{it}) \right) \end{aligned} \quad (2a)$$

$$\begin{aligned} \text{BN demand}_{it} &= \text{Demand}_{b_{it}} + \text{demand}_{s_{it}} * I(\text{Amazon\_Price}_{it} > \text{BN\_Price}_{it}) \\ &= M_i \left( b(\text{BN\_Price}_{it})^{e_b} + s(\text{BN\_Price}_{it})^{e_s} I(\text{Amazon\_Price}_{it} > \text{BN\_Price}_{it}) \right) \end{aligned} \quad (2b)$$

Here  $I$  is an indicator function that takes the value of 1 if the condition is true and 0 otherwise. To identify the coefficients in equation (2a) and (2b), we use a difference-in-difference approach to cancel out unobserved product heterogeneity  $M_i$ . Taking the log of the difference of the two equations, we have the following:

$$\begin{aligned} \log(\text{Amazon\_Demand}_{it}) - \log(\text{BN\_Demand}_{it}) &= \\ \log \left( a(\text{Amazon\_Price}_{it})^{e_a} + s(\text{Amazon\_Price}_{it})^{e_s} I(\text{Amazon\_Price}_{it} < \text{BN\_Price}_{it}) \right) &- \\ \log \left( b(\text{BN\_Price}_{it})^{e_b} + s(\text{BN\_Price}_{it})^{e_s} I(\text{Amazon\_Price}_{it} > \text{BN\_Price}_{it}) \right) \end{aligned} \quad (3)$$

After adding an error term, equation (3) can be empirically estimated. The equation is non-linear in nature and we use maximum likelihood estimation to identify its coefficients.

Towards this, we first estimate consumer demand. However, neither Amazon nor BN report their direct demand data. An emerging stream of work has addressed this problem by extracting the ordinal sales rank information for each product that each retailer provides and devising a way to map the observable sales rank to the corresponding number of books sold. In all cases, researchers find a stable relationship between the ordinal sales rank of a book and the cardinal number of sales, using the following Pareto relationship:  $Quantity = \delta \cdot Rank^\theta$ . (Chevalier and Goolsbee (2003), Brynjolfsson et al. (2003), Ghose et al. (2006)), use  $\theta = -0.871$ . For our study, we continue to use the same parameter for imputing demand for books.

<b>Table 2: Demand Decomposition</b>		
<b>Coefficients</b>	<b>Estimates</b>	<b>Estimates</b>
Market share of loyal Amazon Customers (a)	0.51*** (0.00)	0.51*** (0.00)
Market share of Shoppers (s)	0.02*** (0.01)	0.02*** (0.01)
Price elasticity of Loyal Amazon Customers (e <sub>a</sub> )	-0.88*** (0.01)	-0.81*** (0.01)
Price elasticity of Loyal BN Customers (e <sub>b</sub> )	-1.20*** (0.01)	-1.16*** (0.01)
Price elasticity of Shoppers (e <sub>s</sub> )	-0.57*** (0.02)	-0.52*** (0.02)
Brand premium		0.56*** (0.02)
<b>R-square</b>	63.03%	63.08%

Standard errors are listed in parenthesis below the parameter estimates; \*\*\* denotes significance at 1%.

Column (1) in Table 2 reports the results from this estimation. The results indicate that both Amazon and BN have significant number of loyal customers (or customers with high search costs) with only 2% of shoppers in the market. To be very clear, this 2% refers to the percentage of the population of online book buyer (estimated at about 20% of the entire book market) who are interested in those books that are stocked by both Amazon and BN.com. The results



explain finding of earlier studies that suggests little cross-price elasticity between Amazon and BN. We also note that there are significant differences in price elasticity across different types of consumers. Loyal BN customers are much more price sensitive than loyal Amazon customers. As a result, while BN has about the same number of loyal customers (47%) as Amazon (51%), the realized demand for BN is much lower. The results suggest that there are a significant number of customers with high friction costs in online book markets.

A key feature of this model is the assumption that shoppers switch to the retailer with the lowest price. This assumption implies that shoppers have no brand preference (or search cost) and the two retailers are homogeneous except for the prices they charge. To test the robustness of the model, we relax this assumption and allow shoppers to have a brand preference. Without loss of generality, we assume that shoppers will switch to BN if and only if the difference between BN price and Amazon price exceeds a certain threshold,  $d$  where  $d$  can be construed as the price premium that Amazon can command. Equation (3) therefore takes the following form:

$$\begin{aligned} \log(\text{Amazon\_Demand}_{it}) - \log(\text{BN\_Demand}_{it}) = \\ \log\left(a(\text{Amazon\_Price}_{it})^{\epsilon_b} + s(\text{Amazon\_Price}_{it})^{\epsilon_s} I(\text{Amazon\_Price}_{it} - d < \text{BN\_Price}_{it})\right) - \\ \log\left(b(\text{BN\_Price}_{it})^{\epsilon_b} + s(\text{BN\_Price}_{it})^{\epsilon_s} I(\text{Amazon\_Price}_{it} - d > \text{BN\_Price}_{it})\right) \end{aligned} \quad (4)$$

Column (2) in Table 2 reports the results from this estimation. The results indicate that Amazon enjoys a premium of 56 cents over BN. This finding is consistent with that of Smith and Bynjolfsson (2001) who analyzed data from shopping bots and found that Amazon could command a price premium over BN. It also indicates little changes in estimation of the other coefficients. Thus this analysis confirms that there are major difference in price elasticity between shoppers and customers loyal to either firm. Given that there are differences in price elasticity, this leads to kink in the demand function when shoppers move to or from a retailer.

### Estimation with Kinked Demand Curve

In this section, we develop an empirical model to examine the nature of competition on the demand function.

We use a well-known log-log specification for our demand estimation. The log-log specification has been widely used for estimating demand function and it has the benefits of offering a direct estimation of demand elasticity with the coefficient on the price variable. We can express the demand function as a log linear function between sales rank and product price along with other independent variables:

$$\log(\text{Rank}_{it}) = \beta_{0i} + \beta_1 \log(P_{it}) + \beta_2 \log(T_{it}) + \Omega'X_{it} + \varepsilon_{it} \quad (5)$$

where,  $i$  and  $t$  index product and time. Note that we use book-level fixed effects to account for any unobserved heterogeneity amongst books. The dependant variable is the log of sales rank of product  $i$  at time  $t$ . The independent variables are the retailer price at time  $t$  ( $P_{it}$ ), the number of days since the product was released ( $T_{it}$ ) and a vector of other control variables ( $X_{it}$ ).  $X_{it}$  includes the log of the lowest used product price for a given product, the consumer rating for the product, the log of the number of reviews, and the log of the number of used products offered for sale. The multiplicative product of coefficient on retailer price  $\beta_1$  in equation (5) and the Pareto parameter  $\theta$  represents its price elasticity.

Stiglitz (1989) suggested that market frictions such as search costs lead to a kinked demand function. When friction costs are high, information on price reductions disseminates slowly among potential customers, but price increases are immediately observed by current customers. As a result, a firm in a high friction costs environment faces lower price elasticity for price reductions than for price increases. This often happens for smaller and lesser-known firms whose price information is not well followed by the market. On the other hand, when friction costs are low, information on price reductions disseminates quickly and attracts not only a firm's own regular customers but its competitors' customers as well. This results in higher price elasticity for price reductions than for price increases. This phenomenon is often observed for market leaders whose price information is well tracked by customers and third-party websites.

We allow demand elasticity for price reductions to vary from that for price increases. To do so, we construct a dummy variable *PriceDecrease* which takes the value of 1 if the most recent action on product *i* is a price decrease. We note that the kink happens at the price change point, which indicates that the slope for price decrease from the price change point is different from the slope for price increases from the price change point. Let the price before the most recent price change be  $\underline{P}_{it}$ . We can then modify equation (2) to the following form to capture the changes in price elasticity in the demand function:

$$\log(\text{Rank}_{it}) = \beta_{0i} + \beta_1 \log(P_{it}) + \beta'_1 (\log(P_{it}) - \log(\underline{P}_{it})) \times \text{PriceDecrease}_{it} + \beta_2 \log(T_{it}) + \Omega'X_{it} + \varepsilon_{it} \quad (6)$$

Here  $\beta_1$  represents demand elasticity for price increases.  $\beta'_1$  denotes the difference between demand elasticity for price reductions and that for price increases. A negative value of  $\beta'_1$  indicates the retailer faces higher price elasticity for price increases than price reductions, consistent with the high friction costs scenario analyzed in Stiglitz (1989). If  $\beta'_1$  is positive, it indicates that the retailer faces a higher price elasticity for price reductions than price increases, consistent with the predictions of the low friction costs scenario. Note that this framework also enables us to make a distinct contribution to the prior literature on demand estimation which has typically considered a constant level of price elasticity for either a price increase or a price decrease.

The presence of friction costs also suggests that it takes time for information on price reductions to spread in the market. To quantify this information diffusion process, we consider how demand elasticity evolves over time after a price change. We allow demand elasticity to vary from week to week for up to 4 weeks after the initial price decrease.<sup>2</sup> This requires the creation of four weekly dummy variables, denoted by *Week<sub>ijt</sub>* to represent the number of weeks after the most recent price decrease. We use the four dummies to extend Equation (3) to capture the changes in price elasticity over time as follows:

$$\log(\text{Rank}_{it}) = \beta_{0i} + \beta_1 \log(P_{it}) + \beta'_{1j} \sum_{j=1,2,3,4} (\log(P_{it}) - \log(\underline{P}_{it})) \times \text{PriceDecrease}_{it} \times \text{Week}_{ijt} + \beta_2 \log(T_{it}) + \Omega'X_{it} + \varepsilon_{it} \quad (7)$$

While equation (4) considers consumer friction costs, it lacks consideration for competition in the marketplace. In reality, most online retailers operate in a competitive environment. For example, in the book industry, the two largest online retailers are Amazon.com and BN. As mentioned earlier, duopoly and oligopoly theory indicates asymmetric competitor responses could lead to kinked demand curve as well. To control for the competitive implications, we extend Equation (7) to incorporate competitor responses to a price change. In keeping with prior work in this domain (Chevalier and Goolsbee 2003), we incorporate both Amazon and BN's prices into the equations. The competition from remaining online retailers is captured by  $X_{it}$ , which includes book prices from Amazon Marketplace with listings from smaller online retailers.

Equation (7) also does not control for flows and ebbs often observed in the book publishing industry where a recommendation from popular newspaper or an endorsement from talk show host in the mass media could increase a book's demand manifold. These flows and ebbs are unobservable to researchers and they may have a significant influence on estimated price elasticity. To control for such shocks, we take a difference-in-difference approach that takes the differences between sales ranks of Amazon.com and BN as the dependent variable. The differencing cancels out the influence of such unobserved influence and provides a more accurate estimation of the price elasticity. Our differencing approach is similar to Chevalier and Goolsbee (2003). Further, we leverage the nature of our panel data to control for heterogeneity of individual books across the two retailers. This leads to the following estimation model:

<sup>2</sup> The number of weeks is not very critical towards understanding the result. We are interested in finding out whether search costs decrease with time, and this trend is qualitatively similar across different time periods. We choose 4 weeks because our data reveals that BN responds to a price change on Amazon on an average after 30 days.

$$\begin{aligned} \log(\text{Rank}_{A,it}) - \log(\text{Rank}_{B,it}) = & \beta_{0i} + \beta_{A,1} \log(P_{A,it}) + \beta'_{A,it} \sum_{j=1,2,3,4} (\log(P_{A,it}) - \log(\underline{P}_{A,it})) \times \text{PriceDecrease}_{A,it} \times \text{Week}_{A,it} + \beta_{B,1} \log(P_{B,it}) + \\ & \beta'_{B,it} \sum_{j=1,2,3,4} (\log(P_{B,it}) - \log(\underline{P}_{B,it})) \times \text{PriceDecrease}_{B,it} \times \text{Week}_{B,it} + \beta_2 \log(T_{it}) + \Omega'X_{it} + \varepsilon_{it} \end{aligned} \quad (8)$$

where  $\text{Rank}_{A,it}$  is the sales rank of book  $i$  at time  $t$  on Amazon.com while  $\text{Rank}_{B,it}$  is the sales rank of the same book at time  $t$  on BN. The dependent variable represents the relative demand of a book across the two online retailers. Finally, we note that relative ranking of a book may change over time due to difference in demand dynamics. Some books initially accrue higher sales on Amazon.com but later see more sales on BN. Other books experience the opposite trend. To accommodate differences in demand dynamics across books, we allow the coefficient on  $\log(T_{it})$  to vary from product to product. The revised empirical model therefore takes the following form:

$$\begin{aligned} \log(\text{Rank}_{A,it}) - \log(\text{Rank}_{B,it}) = & \beta_{0i} + \beta_{A,1} \log(P_{A,it}) + \beta'_{A,it} \sum_{j=1,2,3,4} (\log(P_{A,it}) - \log(\underline{P}_{A,it})) \times \text{PriceDecrease}_{A,it} \times \text{Week}_{A,it} + \\ & + \beta_{B,1} \log(P_{B,it}) + \beta'_{B,it} \sum_{j=1,2,3,4} (\log(P_{B,it}) - \log(\underline{P}_{B,it})) \times \text{PriceDecrease}_{B,it} \times \text{Week}_{B,it} + \\ & \beta_{2i} \log(T_{it}) + \Omega'X_{it} + \varepsilon_{it} \end{aligned} \quad (9)$$

As before, we use book-level fixed effects to account for any unobserved heterogeneity. The above model implicitly assumes product prices at Amazon and BN are exogenous decisions. This follows the standard approach taken in the literature for demand estimation of Internet product sales (see for example, Chevalier and Goolsbee 2003, Ghose, Smith and Telang 2006). It is possible that price changes decisions are inherently endogenous as product prices are influenced by market demand for their products. To address this issue, we also estimated a simultaneous equation model. Results from the estimation of this equation system suggest that the endogeneity of product prices is not statistically significant, which is consistent with prior work.

## Analysis

In this section, we present the results of our empirical estimations. Specifically, we focus on the impact of market frictions on (i) overall demand structure, and on the differences of its impact across the two retailers, (ii) on sales of more popular versus less popular books.

### Friction Costs and Demand Structure

The estimates are presented in Table 3. Column 1 presents the result of a base case analysis that incorporates the competition between Amazon and BN but does not consider the impact of market frictions. The parameters of interest have the expected signs. The coefficient on Amazon price is positive, suggesting that a price increase leads to an increase in Amazon sales rank relative to BN sales rank, i.e., a decrease in Amazon's sales relative to BN. On the other hand, the coefficient on BN's price is negative, indicating that a BN price increase leads to decrease in Amazon sales rank relative to BN sales rank, i.e. an increase in Amazon's relative sales.

The regression results can be used to calculate the relative price elasticity of the two online retailers. Given that we use relative sales rank as the dependent variable, we need to impute price elasticity based on the Pareto curve in equation (2). Noting that the Pareto curve indicates that the log of demand is a linear function of the log of Amazon sales rank, the relative price elasticity can be calculated as the product of the coefficients from Table 3 and the Pareto parameter  $\theta$ . Thus, using relevant values of  $\theta$ , we see that Amazon's relative price elasticity for books is between -1.49 and -1.89 and BN's relative price elasticity for books is between -1.53 and -1.60. We find that the relative price elasticities for Amazon and BN are both negative and statistically significant, suggesting that, when prices rise at an online retailer, relative sales ranks at that retailer become larger, i.e., relative demand decreases.

Interestingly, the result suggests that the relative price elasticity for Amazon is very close to the relative price elasticity for BN. This however does not necessarily imply the demand dynamics at Amazon are similar to BN. As noted by Chevalier and Goolsbee (2003), the two retailers may have significant differences in their competitive position even if their relative price elasticities appear to be similar. We also note that the relative price elasticity of Amazon in this sample is slightly higher than that obtained in prior research. Given that our sample has a higher proportion of new releases than samples used in earlier studies, this is not surprising. New releases have wider availability online, thereby leading to reduced market power for Amazon and thus higher relative price elasticity.

Columns 2 and 3 in Table 3 consider the presence of kinks in the demand function at points where price change occurs. After allowing price elasticity to be different for price increases as compared to that for price reductions, we find that the differences are significant for both Amazon and BN. We observe that Amazon's relative price elasticity increases after a price reduction. Column 3 shows that the increase in price elasticity for the first week is not statistically significant. However, starting in Week 2, the increase becomes statistically significant. Based on the Pareto parameter of -0.871, the relative price elasticity for Amazon increases to -2.19 in Week 3 and to -2.21 in Week 4.<sup>3</sup> This result corresponds to the low friction cost scenario in Stiglitz's theoretical model where a reduction in price produces higher price elasticity by enabling the firm to poach consumers from its competitors. Our results also show that the increase in price elasticity on Amazon is gradual over time implying that it attracts more consumers over time as information about price decreases disperses among online consumers.

Contrary to the result on Amazon, we find that BN's relative price elasticity decreases after price reductions. Column 3 in Table 3 shows that the decrease in price elasticity is stable over time and statistically significant. Based on the Pareto parameter of -0.871, the relative price elasticity for BN decreases from -1.59 to -0.82 in Week 1 and remains, more or less, at the same level throughout the four-week period. This result corresponds to the high friction cost scenario in Stiglitz's model wherein a large number of potential customers are not aware of price reductions due to high friction costs. As a result, price reductions do not lead a significant increase in sales. Our result also suggests that information about BN price reductions are not disseminated to potential customers with the passing of time, unlike that on Amazon.

The results suggest that market frictions do have a significant impact on consumer demand function in online book markets. Low friction costs allow price information on some online retailers such as Amazon to disseminate quickly among potential customers. Conversely, high friction costs make potential customers less aware of price information from other online retailers such as BN. Our analysis reveals that Amazon and BN face very different demand curves due to difference in friction costs for their price information.

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<sup>3</sup> The relative price elasticity is equal to the Pareto parameter (-0.871) times the sum of the coefficient on Amazon price (2.14) and the coefficient on Week 3 after price decrease on Amazon (0.38).

Table 3: Parameter Estimates			
Independent Variable	(1)	(2)	(3)
$\text{Log}(P_{\text{Amazon}})$	1.33 <sup>***</sup> (0.04)	1.71 <sup>***</sup> (0.11)	2.14 <sup>***</sup> (0.15)
$\text{Log}(P_{\text{BN}})$	-0.64 <sup>***</sup> (0.1)	-1.76 <sup>***</sup> (0.10)	-1.82 <sup>***</sup> (0.11)
$\Delta\text{Log}(P_{\text{Amazon}})*\text{PriceDecrease}_{\text{Amazon}}$		0.37 <sup>***</sup> (0.11)	
$\Delta\text{Log}(P_{\text{BN}})*\text{PriceDecrease}_{\text{BN}}$		0.74 <sup>***</sup> (0.10)	
$\Delta\text{Log}(P_{\text{Amazon}})*\text{PriceDecrease}_{\text{Amazon}}*\text{OneWeek}_{\text{Amazon}}$			0.08 (0.15)
$\Delta\text{Log}(P_{\text{Amazon}})*\text{PriceDecrease}_{\text{Amazon}}*\text{TwoWeeks}_{\text{Amazon}}$			0.28 <sup>*</sup> (0.15)
$\Delta\text{Log}(P_{\text{Amazon}})*\text{PriceDecrease}_{\text{Amazon}}*\text{ThreeWeeks}_{\text{Amazon}}$			0.38 <sup>**</sup> (0.15)
$\Delta\text{Log}(P_{\text{Amazon}})*\text{PriceDecrease}_{\text{Amazon}}*\text{FourWeeks}_{\text{Amazon}}$			0.40 <sup>***</sup> (0.12)
$\Delta\text{Log}(P_{\text{BN}})*\text{PriceDecrease}_{\text{BN}}*\text{OneWeek}_{\text{BN}}$			0.88 <sup>***</sup> (0.12)
$\Delta\text{Log}(P_{\text{BN}})*\text{PriceDecrease}_{\text{BN}}*\text{TwoWeeks}_{\text{BN}}$			0.85 <sup>***</sup> (0.15)
$\Delta\text{Log}(P_{\text{BN}})*\text{PriceDecrease}_{\text{BN}}*\text{ThreeWeeks}_{\text{BN}}$			0.86 <sup>***</sup> (0.17)
$\Delta\text{Log}(P_{\text{BN}})*\text{PriceDecrease}_{\text{BN}}*\text{FourWeeks}_{\text{BN}}$			0.90 <sup>***</sup> (0.15)
No. of Observations	314176	89045	62994
R-square	69%	69%	68%

The dependent variable is  $\text{Log}(\text{Rank}_{\text{Amazon}}) - \text{Log}(\text{Rank}_{\text{BN}})$ . Standard errors are listed in parenthesis below the parameter estimates; \*\*\*, \*\*, \* denote significance at 0.01, 0.05 and 0.10, respectively. All models use product-level fixed effects. The control variables included average customer rating, number of used books available, minimum used price, number of reviews, and days since the product was released in the market.

Our main analysis rests on the hypothesis that the kink in demand function is due to some kind of market friction in online markets. Another possibility could be the presence of a large number of bargain hunters who are waiting for Amazon to reduce its price before they purchase a book. If that were true one would actually expect to see that the price elasticity is the highest in the first week and decreases over time since consumers would buy in the immediate aftermath of a price decrease. In contrast, what the data suggests is that price elasticity after a price reduction generally increases from the first week over the next three or four weeks on Amazon, thereby eliminating this explanation. This is also corroborated by the estimates in Table 2 which show that only 2 % of consumers in the market are the “shoppers” or “bargain hunters” in the book market.

## Market Frictions and Product Popularity

Since the inception of online retailing in the mid-to-late 1990s, product assortments on the web have increasingly become broader and deeper. Internet retailers have nearly unlimited “virtual inventory” through centralized warehouses and drop shipping agreements with distributors. This enables them to offer convenient access to a larger selection of products than brick-and-mortar retailers. For example, small stores stock approximately 20,000 unique titles, and large independent booksellers stock approximately 40,000 unique titles (Brynjolfsson et al. 2003). Large differences in product variety are also seen in music, movies, and consumer electronics products. Even Wal-Mart Supercenters, which can be up to 230,000 square feet in size, only carry one-sixth of the number of SKUs that are carried by Walmart.com (Owen 2002).

It is now well accepted that the Internet reduces search and friction costs for rare and niche books because online consumers are easily able to locate, evaluate, order, and receive millions of books that are not available on the shelves of local bookstores. However, it is not clear whether providing these books is to the online retailers’ advantage since the reduction in search costs also increase price competition between retailers for this group of consumers. If consumers face close to zero search costs, then stocking these books is not necessarily profitable for retailers since reduced search costs increase competition and eat away most of the profit, unless this could be mitigated by the fact that lower search costs could also expand the pool of potential customers (Cachon et al. 2006).

Ideally, online retailers would prefer consumers to have reduced search costs for product information for rare or unpopular products, but incur higher search costs for price information for these rare books. More importantly, online retailers need to compare search costs for price information for rare or niche products with search costs for popular products and use the results to estimate the relative profitability of the two categories of products in order to decide their price and product assortment strategies accordingly. Anecdotal evidence indicates that there may exist significant differences in search costs between popular books and rare or niche books. Popular books are more likely to be advertised and prominently featured by bookstores. This is evident in both online and offline stores. For example, Amazon always features the most popular books on its bookstore homepage. It also has pages dedicated to NY Times best sellers and other best selling book lists. These actions reduce friction costs for popular books more than that for the less popular books.

For concreteness sake, we will refer to two types of products below: *popular products* that have the greatest sales in a particular category and which are likely to be stocked by any retailer; and *unpopular products* that have so few sales they are unlikely to be economically stocked by any offline retailer, these are products in the “Long Tail” of the product sales distribution (Anderson 2006). In order to understand how market frictions vary between popular books versus unpopular books, we conduct a similar analysis as before but on selected sub-samples from our data. Specifically, we split the sample into two sub-samples based on sales ranks. In keeping with the findings of prior work (Brynjolfsson, Hu and Smith 2003), we use 40,000 as the median sales rank cut-off for denoting books that are relatively popular. Books with median sales ranks more than 40,000 at either Amazon or BN are classified as unpopular books. As robustness checks, we also used as cut-off points books with median sales rank of 40,000 at BN as well as median sales rank of 20,000 and 100,000 across both Amazon and BN. Our results are qualitatively similar across different specifications and are omitted for brevity.

Our results reveal that, for unpopular books with median Amazon sales rank of more than 40,000 (Table 4, Column 1), Amazon’s relative price elasticity decreases slightly after a price reduction. However, for popular books with a median BN sales rank of less than 40,000 (Table 4, Column 4), relative price elasticity increases after a price reduction (the coefficient in Week one is 0.38 and statistically significant) and continues to increase over the next four weeks (as seen in both columns 1 and 2). The results indicate a high level of market friction for unpopular books on Amazon, but low level of market friction for popular books. Moreover, the dynamics over the four-week period suggest that information about price reductions on popular books quickly disseminates among potential customers on Amazon, but similar information on price decreases for unpopular books does not spread as fast.

A similar phenomenon occurs for price reductions on BN. We find that BN’s relative price elasticity decreases significantly after a price decrease for unpopular books. The coefficient of relative price elasticity for BN in the 1<sup>st</sup> week is 1.75 (table 4, Column 1) and 2.54 (table 4, Column 2). It tends to increase gradually thereafter, and the increase is relatively stable across the four-week period. On the other hand, price elasticity decreases only slightly for popular books after a price reduction on BN. The coefficient of relative price elasticity for BN in the 1<sup>st</sup> week is

0.25 (table 4, Columns 1 and 2). The results indicate a high level of market friction for unpopular books on BN, but only moderate level of market frictions for popular books on BN.

Overall the difference between popular books and less popular books suggests that the Internet has significantly reduces market frictions for popular books and increases market competition. However, market frictions for rare and niche books remain relatively high. This could turn out to be a boon for retailers in the fiercely competitive online retailing environment. Our finding also suggests an additional explanation for the newly emerging Long Tail phenomenon observed in online markets. The phenomenon is not only driven by consumers' reduced friction costs for *product* information in finding rare and niche products, but also driven by the differences in friction costs for *price* information for popular versus less popular products. The relatively high friction costs for unpopular or obscure books make it a more profitable category for retailers to stock, thus strengthening the benefits accruing to them from increased product variety in online markets.

Table 4: Parameter Estimates Based on Book Popularity				
Independent Variable	Amazon Sales Rank > 40000	BN Sales Rank >40000	Amazon Sales Rank < 40000	BN Sales Rank < 40000
Log( $P_{Amazon}$ )	3.01*** (0.2)	3.21*** (0.21)	1.67*** (0.17)	1.37*** (0.17)
Log( $P_{BN}$ )	-1.4*** (0.14)	-1.79*** (0.17)	-1.73*** (0.15)	-1.51*** (0.13)
$\Delta \text{Log}(P_{Amazon}) * \text{PriceDecrease}_{Amazon}$ *OneWeek <sub>Amazon</sub>	-0.26** (0.1)	-0.48** (0.21)	-0.06 (0.18)	0.38** (0.17)
$\Delta \text{Log}(P_{Amazon}) * \text{PriceDecrease}_{Amazon}$ *TwoWeeks <sub>Amazon</sub>	-0.07 (0.2)	-0.35* (0.2)	0.24 (0.18)	0.76** (0.18)
$\Delta \text{Log}(P_{Amazon}) * \text{PriceDecrease}_{Amazon}$ *ThreeWeeks <sub>Amazon</sub>	0.03 (0.2)	-0.36* (0.2)	0.4** (0.19)	0.92** (0.18)
$\Delta \text{Log}(P_{Amazon}) * \text{PriceDecrease}_{Amazon}$ *FourWeeks <sub>Amazon</sub>	0.14 (0.17)	-0.3* (0.16)	0.6*** (0.2)	0.95*** (0.16)
$\Delta \text{Log}(P_{BN}) * \text{PriceDecrease}_{BN}$ *OneWeek <sub>BN</sub>	1.75*** (0.15)	2.54*** (0.18)	0.25* (0.14)	0.25* (0.14)
$\Delta \text{Log}(P_{BN}) * \text{PriceDecrease}_{BN}$ *TwoWeeks <sub>BN</sub>	1.3*** (0.21)	2.32*** (0.25)	0.51*** (0.18)	0.39** (0.17)
$\Delta \text{Log}(P_{BN}) * \text{PriceDecrease}_{BN}$ *ThreeWeeks <sub>BN</sub>	1.2*** (0.24)	2.21*** (0.29)	0.6*** (0.2)	0.4** (0.19)
$\Delta \text{Log}(P_{BN}) * \text{PriceDecrease}_{BN}$ *FourWeeks <sub>BN</sub>	1.22*** (0.18)	2.14*** (0.22)	0.53*** (0.17)	0.24 (0.16)
No. of Observations	34180	27177	46066	50228
<b>R-square</b>	61%	64%	71%	70%

The dependent variable is  $\text{Log}(\text{Rank}_{Amazon}) - \text{Log}(\text{Rank}_{BN})$ . Standard errors are listed in parenthesis below the parameter estimates; \*\* and \* denote significance at 0.01 and 0.05, respectively. All models use product-level fixed effects. The control variables included average customer rating, number of used books available, minimum used price, number of reviews, and days since the product was released. The number of observations vary in each table depending on the number of books belonging to each of the two defined kinds of popular and unpopular categories.

## Discussion

A fundamental premise of economic theory is that market becomes more efficient when market friction decreases. Empirical evidence on consumer behavior with online shopping environments is, however, in contrast to theoretical predictions. For example, by examining the shopping patterns of online users over time, Johnson et al. (2004) found that the amount of online search is actually quite limited. On average, “households visit only 1.2 book sites, 1.3 CD sites and 1.8 travel sites during a month in each product category” (Chiang 2006). Another study by Jansen et al. (2000) revealed a similar pattern from the analysis of Web queries by Excite users. Most users had only a few queries per search, and 76% of users did not go beyond their first and only query.

These findings suggest that consumers face friction costs in online markets which often manifest itself, among other ways, in the form of high search costs or brand loyalty towards a retailer. While the Internet clearly facilitates search and has the potential to reduce brand loyalty, it also allows firms to adopt a number of strategies that make search more difficult and enhance consumer brand loyalty (Ellison and Ellison 2004). However, little is known how the friction costs affect consumer demand and online retailers’ competitive strategies. Our paper models and empirically tests this phenomenon by analyzing the nature of the underlying demand function in electronic markets. Using a dataset from Amazon and BN, we show market frictions produce significant differences in price elasticity for price reduction versus price increases. By examining changes in price elasticity at points where prices change, we make a distinct contribution compared to prior literature in online demand estimation that has typically considered a constant level of price elasticity for price increases as well as for price decreases.

Our results suggest, for some retailers like Barnes and Noble online, the presence of a kink in the demand function results in higher price elasticity for price increases than price reductions. This type of phenomenon indicates that consumers face high search costs for price information of those retailers or high levels of brand loyalty for their competitors. For others, market frictions lead to lower price elasticity for price increases than price reductions. This type of phenomenon indicates that consumers face low search costs for price information of such retailers or have a low level of brand loyalty for their competitors. Our analysis indicates that retailers need to recognize that price elasticity for price increases could be very different from that for price decreases and account for the difference while setting optimal price and product assortment strategies.

We also find that price elasticity increases over time after a price reduction for some retailers, but not for others. This suggests that while the Internet has dramatically reduced market frictions for consumers, it would be incorrect for all retailers to assume that their price information will be disseminated among potential consumers just as easily as product information. This may be true not only for smaller retailers, but also for larger, more established retailers. The dramatic differences in the impact of friction costs on two similar retailers indicate that the market frictions can be influenced by online firm. It is possible that the presence of friction costs leads to consumers stay loyal to the largest online retailer (e.g. Amazon) but not to those of the comparatively smaller online retailers. If that were indeed the case, it would suggest that the Internet might not have leveled the field for online retailers to the extent predicted by prior research. This highlights the importance of considering better strategies to disseminate price information to consumers.

## Implications

The Internet facilitates the discovery of lesser-known and obscure products. It has been argued that collectively these less popular products could make up a significant portion of sales for online retailers, known as the “Long Tail” phenomenon (Anderson 2006). To extract meaningful gains from this new opportunity, retailers need to adjust the distribution of product sales and determine the optimal level of product variety. Importantly, while prior studies on the Long Tail phenomenon focus on consumer demand for less popular products, they have typically not considered retailers’ incentives to provide such products. Our analysis reveals that consumers in electronic markets incur higher levels of friction costs on unpopular books than on popular books under the assumption that prices constitute the key purchase criterion for both kinds of products. Given that the former are less likely to be stocked by offline retailers and are more likely to be available online, this finding can have implications for the optimal product variety, assortment planning and inventory management policies for online retailers. Our finding empirically confirms that price competition between retailers for these niche products will be lower, thereby leading to higher



profitability from selling such products. Rather than focusing on promoting popular books that face aggravated price competition, online retailers might be better off by reallocating product assortments towards niche products to take advantage of milder price competition. Businesses can strategically manipulate friction costs for niche products by marketing them under different brand names with differentiated features. Alternatively, retailers can engage in price obfuscation—practices that frustrate consumer price search—resulting in much less price sensitivity on some other products (Ellison and Ellison 2004).

### ***Limitations***

The paper has a few limitations, which may be examined in future research. In particular, we consider the impact of market frictions only across two online retailers. Our dataset prevents us from considering the impact of market frictions on other retailers and from identifying the role played by price comparison engines, which make it possible for consumers to obtain prices from multiple vendors for a given product. While our results have effectively incorporated the impact of shopbots on overall consumer demand, we do not know their exact influence on consumer demand. We realize that the number of unique books listed by a shopbot is significantly lower than the inventory of Amazon. For example, Dealtime, a leading shopbot for books, displays only 1.39 million unique books, far fewer than the 3.6 million unique books available on Amazon. That potentially lends further support to our finding that friction costs are higher for less popular or niche books compared to the popular ones.

Another limitation of the paper is that while we show friction costs vary significantly across online retailers, we do not have data to pinpoint the exact causes for the phenomenon. It could well be due to consumers' preferences for searching only the more well known and branded online retailer, which creates significant variations in the nature of the demand structure across online retailers. Alternatively, it could be due to the intrinsic differences in the type of consumers that the different online retailers attract. For example, Amazon may attract more tech-savvy consumers who are better at searching for lower prices, while BN's clientele could be less experienced in searching online for price information. It is also possible that the recommendation systems and co-purchase networks prevalent on Amazon reduce price search costs and other friction costs for consumers on its website. Similarly, there is some evidence that the volume of conversations in blogs are correlated with of books at Amazon, and thus blogs may be indirectly expediting the spreading of any price information at Amazon across the market (Gruhl et al. 2005). A deeper exploration of the causes of friction costs across online retailers could be a fruitful area for future research.

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